DIAGNOSTICS AND DATA FUSION OF ROBOTIC SENSORS

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ABSTRACT

Robotic systems for remediation of hazardous waste sites must be highly reliable to avoid equipment failures and the subsequent possible exposure of personnel to hazardous environments. Safe and efficient clean-up operations also require accurate and complete knowledge of the task space. This paper presents the results of a program, sponsored by the Department of Energy (DOE) Federal Energy Center (FETC), to meet these needs. To enhance robot reliability, a conceptual design of a monitoring and diagnostic system has been developed to predict the onset of mechanical failure modes, provide maximum lead time to make operational changes or repairs, and minimize the occurrence of on-site breakdowns. To ensure safe operation, a comprehensive software package has been developed to fuse data from multiple surface mapping sensors and poses so as to reduce the error effects in individual data points and provide accurate three-dimensional (3-D) maps of a work space.

I. INTRODUCTION

The safe and cost effective cleanup of hazardous waste sites within the U. S. nuclear weapons production complex requires the use of remotely controlled robotic systems. These robotic systems have to be robust to stand the demands of the hostile environment. Due to the physical dangers associated with the waste site surroundings, failed robots are not easily accessed by humans to perform repairs and in extreme cases may have to be hauled out by other robots or abandoned altogether. Monitoring and diagnostic systems are the only means of providing early stage detection, isolation, and tracking of developing faults before they result in catastrophic failure.

A typical decontamination and decommissioning (D&D) task involves facilities that contain a complex maze of pipes, valves, gages and tanks supported on large steel structures. Because of the uncertain knowledge of these facilities, due to incomplete and/or missing records, sufficient information about the task space has to be generated in situ to allow collision free movement and sensor based grasping to support dismantlement activities. Task and tooling needs can only be determined as more information is revealed about the site. The robotic actions, in addition, must be performed with high confidence due to the extreme safety hazard.

To address the above demanding requirements, DOE has undertaken the development of a model-based supervisory control architecture. The key elements of this architecture are the inclusion of an operator in the control loop, a three-dimensional (3-D) "world model" of the task space, surface mapping sensors to generate topological information, a data fusion and a visualization software module to integrate sensor data and confirm and update the world model, and monitoring and diagnostic technologies to provide information about robot health. The overall development approach and the results achieved on the data fusion software module and the monitoring and diagnostic technologies are described below.

II. DATA FUSION SOFTWARE MODULE

When a surface mapping sensor scans a scene, the resulting data is expressed in the coordinate frame associated with the sensor's physical location and orientation. If the sensor moves, then any subsequent data will be expressed in a different coordinate frame related to the new location and orientation. Therefore, an essential requirement for combining data sets from different poses is to first convert all data into a common coordinate frame. This process, called data (scene) registration, requires the computation of the transformation that exists between two sets of data acquired from different poses of the sensor. Although registered data from multiple sensors/poses can be combined directly without any further processing, a fusion algorithm that weights sensor error can achieve significantly better results by reducing the effects of error in individual data points. Such an algorithm thus provides a more accurate map of the work space.

The development objective for the data fusion module was to produce software that performs data registration and data fusion functions for robotic remediation systems. To provide the most flexibility for different applications, the data fusion module that has been developed contains three components: a registration software component, a fusion software component, and a graphic user interface (GUI) software with file management capability. Each of these software components is described below.

A. Registration Software Component

The registration software component serves two operational needs: to transform the data into a common representation to permit the creation of a composite map of a task space, and, to locate a robot in that task space. The first need arises from the requirement of accurately combining data from multiple sensor scans, acquired from different poses within a task space, in order to build a 3-D representation of the task space that is adequate for subsequent planning and execution activities. In this case the registration process determines the relative transformation that exists between two or more data sets acquired from different sensor poses. The second need arises from the requirement of accurately locating a robot by means of measurements from a sensor mounted on its end effector. In this case, the registration process estimates the pose of the robot end effector by determining the transformation between the data generated by its sensor and a set of corresponding spatial coordinates stored in the GUI control files.

At the outset of this project, an evaluation of the available registration algorithms and software was made to identify the best technical solution compatible with the schedule and cost constraints of the project. Because the preferred solution is a package of appropriate algorithms and codes that have already been developed and tested, inquiries were made with key members in the DOE robotics community. This interaction identified the following six registration algorithms:

Feature Based Algorithm. Developed by Mechanical Technology Incorporated (MTI) for Topographical Mapping Systems, this technique uses three or more naturally occurring noncolinear objects in the task space of simple geometric shapes, common in the two data sets, to derive the transformation[1] that will bring the coordinate frames of the two data sets into coincidence.

Iterative Closest Point (ICP) Algorithm.[2] Improved by Carnegie Mellon University (CMU), this technique was devised to avoid the problem of feature extraction for high-speed applications. Scanned data is matched to a model of a free-form surface, using an iterative, least-squares ICP algorithm.

ICP plus Spherical Attribute Image (SAI).[3] Developed by CMU, SAI is a technique for registering scenes which have no features or fiducials, but only free-form objects.

Geometric Hashing. Developed by CMU, this algorithm provides a means to automate the registration process by fitting data to a member of a library of objects. The technique provides a good initial estimate of the pose which is refined by the ICP algorithm.

Coleman Research Corporation (CRC) Approach. In this approach, registration is done with the help of artificial targets placed in the work space. These targets are typically spheres whose centers are the fiducial points. With corresponding data points, the pose is estimated via an iterative, least-mean-square technique.

Fourier Transform.[4] Developed by the University of Florida, this technique was devised for efficient updating of robotic world models. The Fourier transform technique is used to register the two images (in scale, rotation, and translation), so that a subtraction will reveal the changes present in the current configuration.

Based on the comparative evaluation of the above techniques, their states of development, and programmatic risk considerations, the feature-based registration technique was selected. This technique is a four-step process that requires algorithms for feature data segmentation, feature surface characterization, computation of fiducial points, and computation of the transformation (pose estimation) required to converge the two data sets. The following operational scenario illustrates this approach.

1. Using existing facility drawings, video images, and 3-D visualization software, a set of reference targets are identified. These targets are naturally occurring objects of simple geometric shapes having features that allow computation of fiducial points. (A target has features which define a fiducial. For example, the intersection of two pipes contains two cylinders, whose closest approach defines a line segment whose mid-point is a fiducial.) The design supports the following set of reference features.

- Corner formed by three walls. The components are three plane surfaces. The fiducial is the point where the line formed by the intersection of two of the planes intersects the third plane.

- Pipe intersecting a wall. The components are a cylinder and a planar surface. The fiducial is the intersection of the axis of the cylinder with the plane.

- Intersection of two non-parallel pipes. The components are two cylinders while the fiducial is the midpoint of the line connecting the closest approach of the two non-parallel cylinder axes.

- Cylinder intersecting an end-cap or dome. The components are a cylinder and a quadric surface. The fiducial is the intersection of the cylinder axis with the quadric surface.

2. For each target feature component in each data set, the system operator encloses the relevant data in a region-of-interest box. The enclosed spatial data is segmented and output to the registration software.

3. Geometric forms are fit to the segmented data (plane, a quadric surface, or a cylinder) and the fiducial points computed. The output of this algorithm is the estimated position of the fiducial point and a goodness of fit metric.

4. The corresponding fiducials in the two data sets of interest are identified and forwarded to the pose estimation algorithm that computes the transformation between the two sensor poses.

The individual elements in the fiducial algorithms and the pose estimation algorithm were coded and checked. Upon completion, individual modules were validated at the unit level using simple test data sets. At the system level, more complex task spaces were modeled, including existing mapping data from the acid fractionator at ORNL and the piping mock-up at CMU. The feature-based registration technique proved to be effective in each case.

B. Fusion Software Component

The purpose of the fusion software is to convert sensor measurements of the geometry of the task space into a 3-D spatial data representation, called occupancy maps. These occupancy maps store a scalar parameter, the probability of occupancy, the value of which indicates, to various degrees of certainty, the areas that are free regions and the areas where encounters with solid surface is likely. Along with the occupancy map, the software computes a 3-D confidence map. The scalar value stored in each cell of the confidence map represents the degree to which the corresponding probability of occupancy value is supported by the source data. The 3-D occupancy map and 3-D confidence map are basic outputs of the fusion software that can be interpreted through visualization using the Interactive Computer-Enhanced Remote Viewing System (ICERVS), developed by MTI under separate DOE funding (DE-AC21-92MC29113). In summary, the fusion software requires the following three key elements, the sensor error model, the occupancy map algorithm, and the confidence map algorithm.

1. Sensor Error Model. The sensor error model is a user supplied external function which is dynamically linked to the Fusion Software Module at the run time. The sensor error model is specific to each sensor and contains the effects of many factors including basic sensor physics, its mechanical repeatability, the target surface roughness, color, and reflectance, and the environmental effects such as task space temperature and humidity.

Surface mapping sensors selected by DOE for facility mapping system include a laser radar and a structured light sensor. For the laser radar, the typical error sources after calibration include noise in the light detection hardware, mechanical scanner jitter, signal attenuation from surface tilt and curvature, and variation in speed of light due to changes in temperature and humidity. For structured light sensor the errors include quantization error associated with the basic optical resolution, mechanical positioning errors, and the surface induced distortion of the laser illumination. In general these errors have Gaussian distribution in the three orthogonal directions and can therefore be spatially described by three variance values. Given the coordinates of a measured point, the sensor error model will compute the set of variances associated with the range, azimuth, and elevation of the particular point. These variances are used to generate probability density function using Gaussian uncertainty distribution.

Since the surface and environmental effects induce significant errors, the sensor error model, for it to be useful, needs to be based on experimental characterization. For the present project, the sensor error model for the structured light sensor is based on work performed at MTI for the development of a Topographical Mapping System (TMS). The laser radar sensor error model is based on the results obtained from the Oak Ridge National Laboratory (ORNL) testing of a Coleman FM laser sensor.

2. Occupancy Map Software. Given a set of sensor measurements and the associated sensor error model, the occupancy map algorithm constructs a three dimensional occupancy grid where each cell in the grid is characterized by the probability that it is occupied. A value of "0" indicates that the cell is known to be unoccupied or empty, while a value of "1" indicates that the cell is known to be occupied or full. Initially, the probability of occupancy for all cells is set equal to 1/2 and flagged as unmapped.

To create the occupancy map for a data set, the fusion software retrieves the sensor error model for that sensor and determines the error variances for each point. This permits the computation of a spatial occupancy profile for a data point that also reflects the fact that the sensor must have a clear line of sight to that data point. This computation is repeated for each data point to create the occupancy map for that data set. Data fusion is performed when the individual occupancy maps such as those described above, are combined using Bayesian integration, to form a fused occupancy map.

Algorithms required for implementation of the Fusion software were defined first. Prototyping effort of the 2-D and 3-D version of the algorithm indicated a need to preprocess the sensor data for conflict resolution, which has been developed and implemented. The occupancy map software was designed, developed and successfully implemented.

3. Confidence Map Software. Development of Confidence Map software was subcontracted to Dr. Mongi Abidi of University of Tennessee-Knoxville.

For each cell in the confidence map, a confidence metric is computed to estimate the extent to which the corresponding probability of occupancy value can be presumed valid. The confidence metric reflects the relative insensitivity of the probability of occupancy to the assumptions made in computing it. These assumptions include, for example, the parameter values chosen in the sensor error model. This work was successfully accomplished and the results integrated in to the remainder of the software.

C. Graphic User Interface

The ICERVS GUI was expanded to provide a user friendly interface to the Data Fusion module. The system architecture integrates the Data Fusion Module with ICERVS and provides a seamless interface between the two systems and the user. The GUI interacts with both the Registration and Fusion software.

Figure 1 illustrates the concept of visualizing registered and fused data using synthetic data. The left side of the figure shows data from two sensor locations that, when properly registered, provide the user with an integrated scene that contains information that would be hidden from either one of the sensor locations alone. The right side of the figure shows the results of fusing this data. The color bar at the bottom of the figure shows percent occupancy, with blue indicting that their is good confidence that the space is unoccupied, and blue indicating high confidence that the space is occupied (i.e., the surface of a mapped object).

Figures 2 and 3 show data obtained from a laser range finder that was used to map a piping mock-up at CMU. The lower left portion of Figure 2 shows an overlap of three poses. The upper portion shows an enlargement of a portion of the image, with fiducial points more clearly visible. The right side of the figure shows a registered scene of all three poses, with the result being a more clear representation of the actual mock-up. Figure 3 shows associated occupancy and confidence maps of this scene. In essence, the occupancy map contains estimates of the likelihood of cell occupancy while the confidence map expresses the trustworthiness of the estimates.

III. MONITORING AND DIAGNOSTICS

The simplest form of condition monitoring of robots is implemented by periodic inspections. Periodic inspections comprise an important part of maintenance programs because they effectively detect problems that provide visible evidence before affecting operation (cracked hoses, leaky seals, dust-clogged radiators). Periodic inspections obviously offer no value if a sudden failure occurs during operation.

Limit-checking of onboard sensors is the next step and another important part of condition monitoring of robots. With this approach, a fault is assumed to have occurred if a sensor measurement exceeds a prespecified threshold value. Limit-checking is typically employed to protect against sudden overload, control breakdowns, and serious operator errors by annunciation or shutting down the system in trouble when thresholds are exceeded. The main advantages of using limit-checking is that it is computationally simple to implement and provides protection when major faults occur; however, this is often too late to avoid serious operational problems and work interruptions. Rosie currently has several onboard sensors; however, these are only used for motion feedback.

Developing a practical monitoring and diagnostic system for the mobile robot system is a complex task. A successful system will use several approaches ranging from simple limit checking for certain failure modes to some of the more advanced techniques that are discussed below. Optimum robot reliabilities will be achieved when deployment of such a system is done in combination with a maintenance program which includes at least some periodic inspection.

The system design effort was preceded by the following steps: a) analysis of D&D robots, represented in this case by the Rosie mobile worksystem developed by Redzone Robotics and CMU, to determine failure modes, relative criticalities, and fault-symptoms; b) review and evaluation of the current literature to search out applicable diagnostic and prognostic methodologies; c) specification of the system requirements; and d) development of a design strategy.

The following subsections note the results achieved in these areas.

A. Identification of Component Failure Modes

One of the most important aspects in the analysis of robot failure modes is the criticality of different components and different failure modes to robot operation. Establishing a criticality ranking is necessary to ensure that the monitoring and diagnostic system gives highest priority to those failure modes with the greatest effect on robot operation.

To develop failure mode criticality and fault-symptoms, information was gathered from several sources and put into a relational database. Engineering data describing the design of the Rosie platform was supplied by Redzone Robotics.

A functional schematic was generated describing each major subsystem and function path. A Component Application Table was generated listing each mechanical element. Generally, the breakdown stopped at the individual components as assembled onto the platform such as the wheel drive motor rather than smaller pieces such as rotors, housings, seals, bearings, etc. This generally worked well as failure mode data are available describing such mechanisms as complete components. A criticality level was defined which placed each component in one of three categories based on failure effects: 1) possible damage to robot or work area, self removal may not be possible; 2) work assignment cannot be completed, self removal may be possible; and 3) work assignment can be completed, maintenance is necessary.

A Possible Failure Modes Table was also put together. For each component, this table lists each failure mode that is thought to be reasonably possible within the existing application. Various sources in the open literature and MTI internal reports were used as sources for this data. The information for each failure mode lists the failure data for several representative component types. Primary cause and symptoms are given. The former generally serves to complete the definitions of a given failure mode. Speed of failure and probability of failure are also included in the table. The former is given as either sudden or gradual and provides the logical basis to prompt the diagnostic system to act quickly for sudden faults while allowing additional diagnostic time for gradual failure modes. Probability of failure is assigned as low, medium, or high and is based on a qualitative assessment of the failure mode for the application.

The Component Application Table and the Possible Failure Modes Table were combined to form a Master Component Failure Mode Table. This combines some 600 system failure modes. As the design process proceeds a down-selection of the most important failure modes should be made to keep the system to a manageable size.

B. Identification of Applicable Technologies

A survey was conducted to identify monitoring and diagnostics systems available in the literature for robot manipulators. The literature survey revealed diagnostics methods for robots in four broad areas: dynamic model-based diagnostics, expert systems, pattern classifiers, and hybrid diagnostic systems. In model-based diagnosis, the main motivation is to represent the robot dynamics in the diagnostic system for early detection of faults. Merits and problems of four model-based methods, namely parameter estimation[5], analytical redundancy [6], stochastic filtering[7], and dynamic thresholds[8] were evaluated.

In the expert systems area, two types of methods based on shallow and deep knowledge are available. Shallow expert systems derive their knowledge from Fault Trees, Failure Mode and Effects diagrams, Event Trees or if ¼ then rules. Deep expert systems, on the other hand, derive their diagnostic knowledge from the structure and function of the robot components and store it in form of rules for diagnosis. Only one such system was developed by Krishnamurthi and Phillips[9] to address fault diagnosis of robot electronics.

In pattern classification based diagnosis, two methods using fuzzy set theory and neural networks have been applied to robot diagnosis. A fuzzy pattern classifier has been developed by Tzou et al.[10] for detection of abrupt speed changes in the robot using vibration sensors. In the neural network application, a Cerebellar Model Articulation Controller (CMAC) algorithm has been developed for manipulator fault detection.[11]

Hybrid diagnostic methods have been proposed in the literature to overcome the problems associated with individual methods by using combinations of dynamic models, expert systems, and pattern classifiers. Two well-developed hybrid methods are available. Isermann and Freyermuth[12,13] developed a hybrid method using a combination of parameter estimation method and fault-symptom trees to identify abnormality in the robot and relate the abnormality to component faults, respectively. Schneider and Frank[14] proposed a fuzzy logic-based threshold adapting expert system for observer-based dynamic fault detection system. Most of the advanced methods for robot diagnosis are included in a survey by Dhillon and Anude.[15]

The literature survey revealed very few papers in the area of prognostics of robots indicating that this area is not as mature as the diagnostic area. There are two prognostic methods for predicting the reliability of general mechanical components. The first method predicts the failure of a component due to fatigue resulting from cyclic loading using fatigue strength models, whereas the second method uses probability-based models (Gaussian and Weibull distributions) to predict the number of cycles a component will survive.

Although fault tolerance methods are not directly related to fault diagnosis, because of their importance with regard to robot reliability and their abundance in literature, these methods were also reviewed. The review provided information that will be considered in development of a diagnostic system for the Rosie mobile worksystem which has an interface/capability to incorporate fault tolerance algorithms. This interface will allow the diagnostic system to use fault tolerance algorithms for on-line identification of components critical to the mission in the presence of impending component failures. Based on information obtained from the literature review, a list of diagnostic methods applicable to the Rosie mobile worksystems have been compiled along with a list of possible sensors for monitoring the worksystem. This list currently includes position sensors (encoders, resolvers), tachometers, flow sensors, pressure sensors, liquid level indicators, vibration sensors, acoustic sensors, etc. A trade-off study has been conducted to understand the relevance and applicability of the various diagnostic methods to the Rosie mobile worksystem. The study included the types of sensory signals these methods operate on, the signal preprocessing required, the computational requirements of these methods, and their sensitivity to faults.

C. Design Strategy and Conceptual Design

In order to develop a design strategy for a diagnostic system, a set of design requirements are needed. For the Rosie mobile worksystem, these design requirements were developed based on the operational requirements of a robot to be used for D&D, the literature survey, discussions with the customer and the end user, and prior MTI experience in the area of diagnostics. The following design requirements have been identified for developing a diagnostic system for the Rosie mobile worksystem:

- The diagnostic system must operate on-line.
- It must give indication of critical failures at the earliest possible time.
- It must have the ability to cope with the dynamic nature of robot operation.
- It must be able to represent complex relations between faults and sensors signals.
- It must be able to use approximate diagnostic information in the form of approximate probability of failure values and failure propagation rates.
- It must have the ability to integrate sensory information (from diverse set of sensors, human input, etc.) into a cohesive diagnostic strategy.
- It must consider the influence of the robot's environment on component failures.

- It must require the least number of sensors.
- It must have an interactive interface for user to enter information he/she perceives through others sensors (e.g., video images).
- It must be computationally inexpensive.
- It must be conducive to integration of prognostic and fault tolerance algorithms.

It is clear from the above list that many of these requirements are in conflict. For example, the ability to integrate various sensors would require large processing time which directly conflicts with the on-line operation requirement. The design of a diagnostic system for the robot aims at achieving a balance between these conflicting design requirements.

Based on the above requirements, a preliminary conceptual design of a diagnostic system has been developed for the Rosie. This diagnostic system is a hybrid between dynamic-model-based methods and shallow expert systems. The dynamic model was used to generate deviations in position/velocity during the robot's operations. Along with other sensor signals (e.g., pressure, temperature, flow, etc.), these deviations were then used for hierarchical fault detection and diagnosis. In the first hierarchy, fault detection will be performed using signals from various robot sensors, while in the second, third, and fourth hierarchies, faulty robot subsystems, components and component failure modes will be identified. A hierarchical diagnostic system was deemed necessary to achieve a good balance between providing fast on-line fault detection and diagnosis and a time-consuming search process required to identify individual faults. A hierarchical design allows fast fault detection to be performed on-line. On detecting a fault, the diagnostic system should immediately inform the operator and then perform the more time-consuming fault diagnosis.

The conceptual design of the diagnostic system was performed, a cost-benefit analysis was conducted to evaluate the cost of implementing the diagnostic system and the expected benefits. Based on estimates of the number of robot units to be put into operation in the near future, the types of operation they would be performing, the expected benefits from the diagnostic system in terms of down time and money saved was evaluated. Also, the hardware/software required to implement the diagnostic system and integrate it with the robot's subsystems has been assessed.

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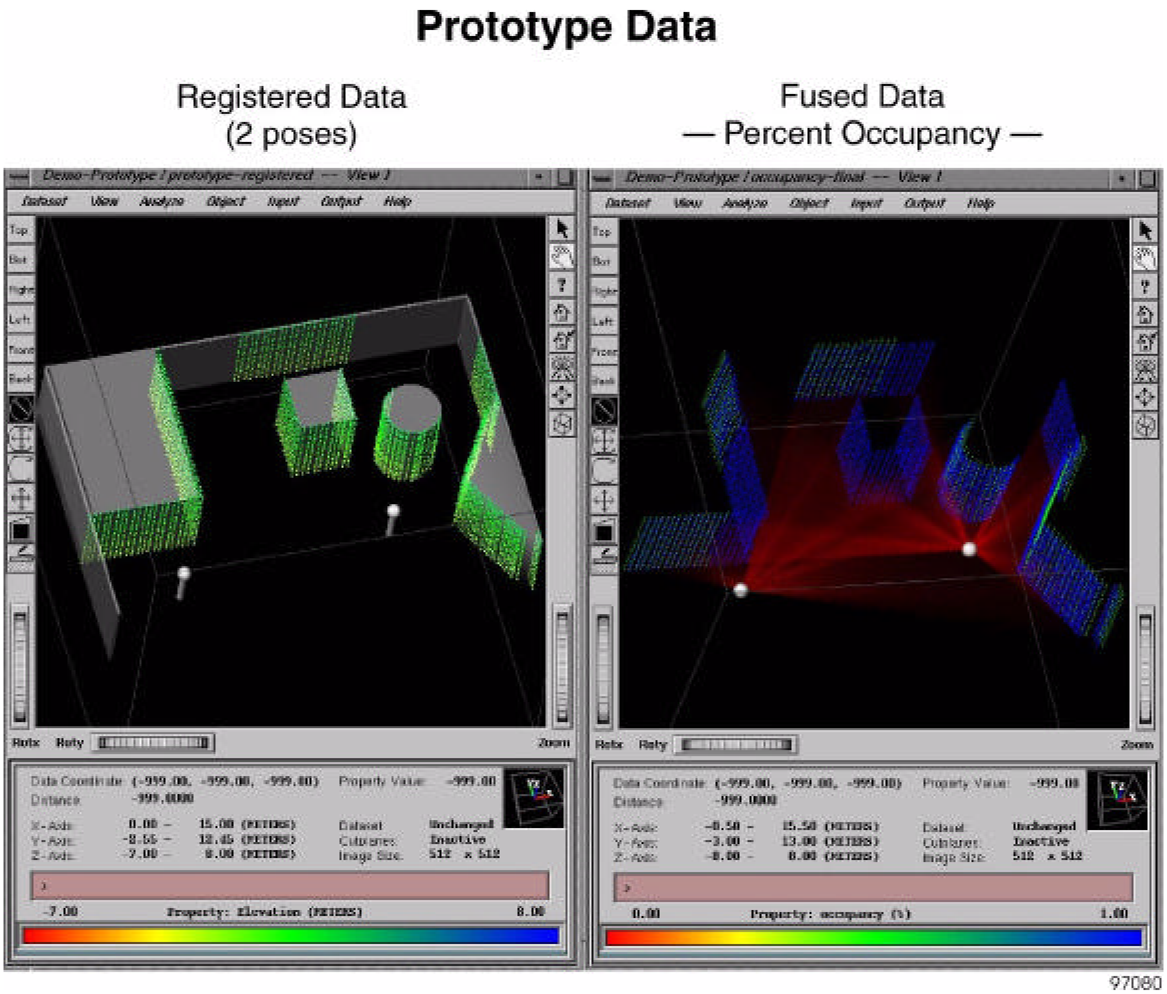

Figure 1. Registered and Fused Data from Two Sensor Locations

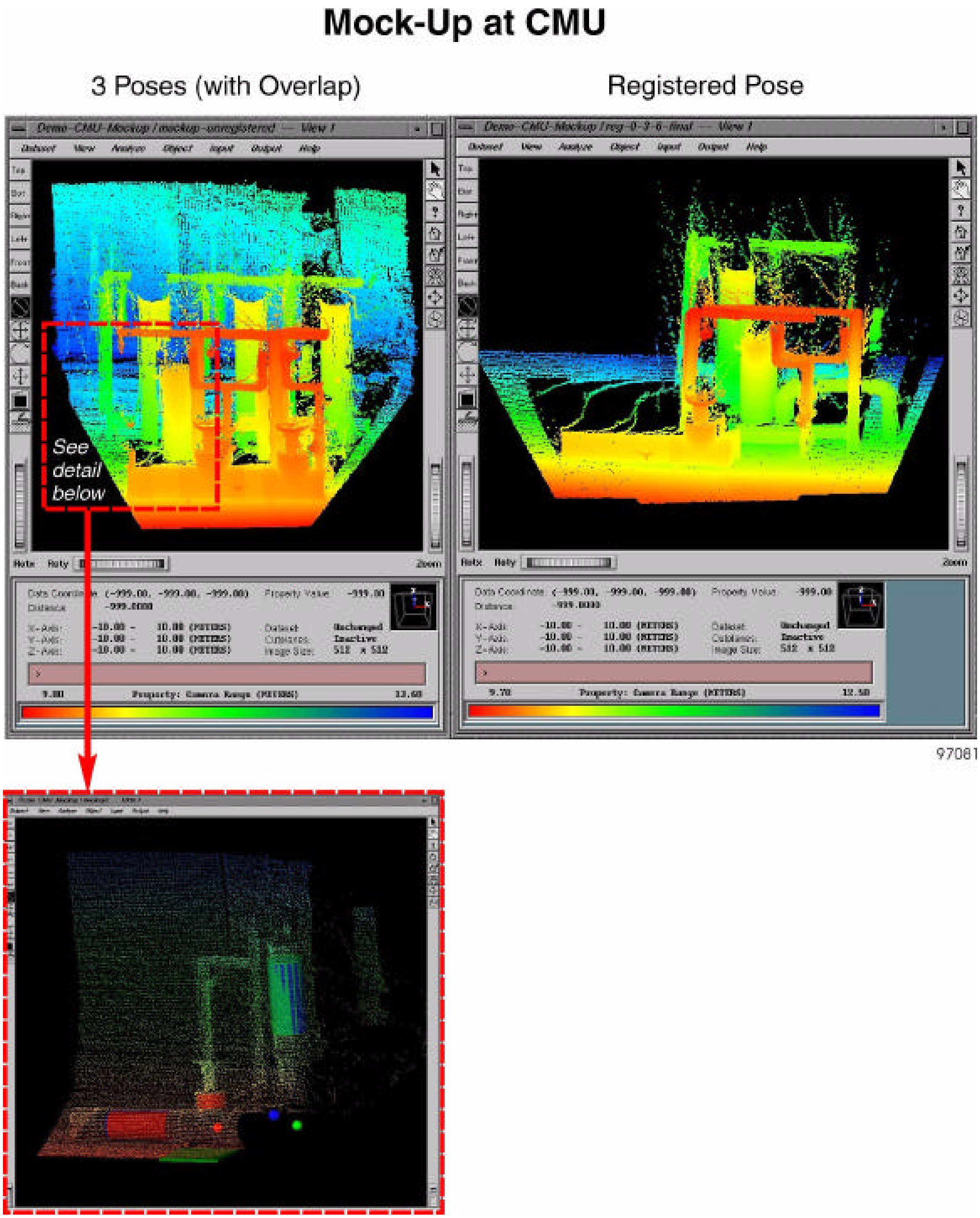

Figure 2. Laser Range-finder Data of Piping Mock-up from Three Poses

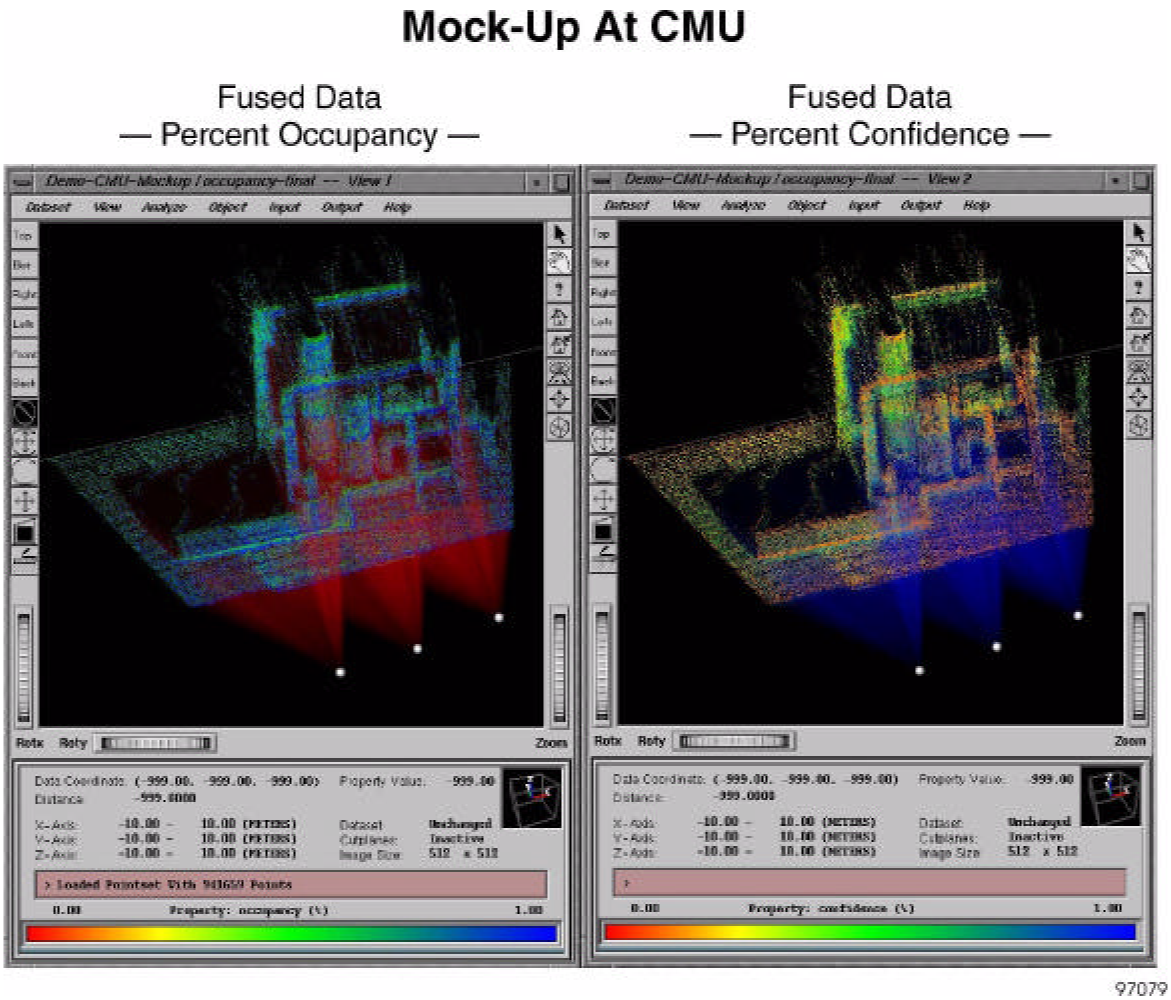

Figure 3. Fused Data from Piping Mock-up